



## The Influence of Artificial Intelligence Tools on Postgraduate Students' Learning Practices in Mogadishu, Somalia

**Abdirahman Abdullahi Ahmed**

Faculty of Economics and Management Sciences, Hormuud University, Mogadishu, Somalia

Email: [abdirahmangarabey@gmail.com](mailto:abdirahmangarabey@gmail.com)

### Abstract

Artificial Intelligence (AI) tools are spreading quickly in higher education and are changing how students search for information, organize academic tasks, write assignments, and support research-related learning. However, empirical evidence of the influence of AI tools on postgraduate students' learning practices remains limited in low-resource and understudied higher education contexts, such as Mogadishu, Somalia. This study examined how AI tools, including ChatGPT, Gemini, Copilot, Grammarly, Claude, and related AI-supported academic tools, are used by postgraduate students and how AI use relates to learning practices. The study used a correlational cross-sectional survey design and analyzed 142 valid responses from postgraduate students in Mogadishu universities. The analysis used descriptive statistics, reliability testing, Pearson correlation, and ordinary least squares regression. Results indicated that AI tool use was common among respondents: 39.44% reported daily academic use, and ChatGPT was the most frequently selected tool (74.65%). AI tools were mainly used for research (71.13%), assignments (49.30%), and reports (43.66%). However, regression analysis indicated that AI use intensity did not significantly predict overall learning practice (coefficient = -0.0989,  $p = 0.2765$ ,  $R\text{-squared} = 0.0085$ ). The only significant dimension-level result was a negative association with assignment completion, coefficient = -0.4843,  $p = 0.0219$ . Reliability coefficients were weak, so composite-scale interpretation should be treated cautiously. The study concludes that AI tools are widely used among postgraduate students in Mogadishu, but frequent AI use alone does not provide clear evidence of improved learning practice. Universities should therefore focus on responsible AI training, academic integrity, and guided use rather than assuming that access to AI tools automatically improves postgraduate learning outcomes.

**Keywords:** Artificial intelligence (AI), Postgraduate students, AI tools, Learning practice, ChatGPT

### 1. Introduction

The rapid advancement of artificial intelligence (AI) has become a major global phenomenon affecting many areas of human life, especially higher education (Future Facing Learning and AI in Higher Education 2026, n.d.). AI tools have redefined how students access information, organize academic knowledge, prepare academic texts, and engage with learning tasks (Ibrahim et al., 2026). Tools such as ChatGPT, Google Gemini, Microsoft Copilot, Grammarly, Claude, summarizers, text generators, and research assistants offer students rapid support for

explanation, drafting, summarization, translation, brainstorming, and academic writing (Lindakumbura, n.d.).

Postgraduate students are expected to demonstrate independent study, critical thinking, research ability, academic writing competence, and responsible learning behavior (Ambe, 2026). Because postgraduate learning is more self-directed than undergraduate learning, AI tools may be attractive to students who need support in searching for academic materials, understanding complex concepts, preparing assignments, and developing research-related outputs (Mwakalinga & Tweve, 2026). In this sense, AI tools may function as learning assistants that support productivity and access to information (Mudenda, 2025). However, the educational value of AI tools is not automatic (Ali & Saleem Mohsin, n.d.). AI tools may also encourage dependency, weak verification of information, surface-level learning, plagiarism, and overreliance on generated text. These risks are important in higher education because postgraduate students are expected to demonstrate original analysis, research competence, and ethical academic behavior. Therefore, it is not enough to know whether students use AI tools; it is also necessary to examine whether the intensity of AI use is associated with stronger learning practice (Sangadji, 2025).

Although studies on AI in higher education are growing internationally, the Somali context remains underrepresented. Universities in Mogadishu are increasingly exposed to digital technologies and generative AI tools, but local evidence about how postgraduate students use these tools is still limited. This study addresses that gap by analyzing survey data from 142 postgraduate students in Mogadishu. The study focuses on AI tool use, learning activities, challenges, learning practice items, dependency risk, and the predictive relationship between AI use intensity and learning practice.

The study is guided by the Technology Acceptance Model and Self-Regulated Learning Theory. The Technology Acceptance Model explains how perceived usefulness and ease of use affect technology adoption (Davis, 1989). Self-regulated learning theory explains how students plan, monitor, and evaluate their own learning behavior (Zimmerman, 2002). These theories are relevant because postgraduate students use AI tools not only as technologies but also as possible learning supports that may shape how they study, complete academic work, and manage research-related tasks.

## **2. Literature Review**

AI in higher education has been studied as a form of educational technology that may support personalized learning, feedback, automation, assessment, writing, and information access. Zawacki-Richter et al. (2019) showed that AI applications in higher education are growing but also noted that educational and pedagogical implications require stronger attention. This is directly relevant to postgraduate learning because the effectiveness of AI tools depends on how students use them within academic practice.

Generative AI tools, especially ChatGPT and similar large language models, have intensified debates about learning support and academic integrity. Kasneci et al. (2023) pointed out that large language models can support education through explanation, feedback, and writing assistance, but they also create risks such as inaccurate content, overreliance, and misuse. Deng et al. (2025) found that ChatGPT may improve several learning outcomes in experimental studies, but such findings do not mean that all AI use produces learning gains in every context. Local empirical testing remains necessary.

The Technology Acceptance Model is useful for understanding why students adopt AI tools. According to Davis (1989), perceived usefulness and perceived ease of use affect the acceptance of technology. In the context of this study, postgraduate students may use AI tools because they believe these tools make academic work faster, easier, and more productive.

Strzelecki (2024) also showed that student acceptance of ChatGPT in higher education is shaped by factors related to technology acceptance and actual use behavior.

Self-Regulated Learning Theory is equally relevant because postgraduate study requires learners to set academic goals, monitor their progress, and evaluate the quality of their own work. Zimmerman (2002) described self-regulated learners as active participants in their learning processes. AI tools may support self-regulation by helping students summarize materials, generate ideas, and structure assignments, but they may weaken self-regulation if students use them as substitutes for independent reading, analysis, and writing. Panadero (2017) also emphasized that self-regulated learning involves multiple models and processes, including goal setting, monitoring, and self-evaluation.

Somali higher education evidence is still emerging. Abdi and Abdullahi (2026) examined generative AI adoption in Somali higher education and highlighted trust, academic integrity, and access constraints as important issues. Wehlie et al. (2026) examined ChatGPT familiarity and academic writing-related outcomes among students in Mogadishu and showed that AI use is becoming a local higher education issue. These studies support the need for empirical analysis of postgraduate students in Mogadishu, especially regarding whether AI use is linked to stronger learning practices or to dependency and weak academic behavior.

Based on this literature, AI tools may influence postgraduate learning practices positively or negatively. They may help students search for information, complete assignments, improve writing, and conduct research (Future Facing Learning and AI in Higher Education 2026, n.d.). At the same time, they may encourage dependency and reduce critical engagement. Therefore, this study investigates the actual pattern in the dataset rather than assuming that AI tools automatically improve postgraduate learning.

### **3. Data and Method**

This study used a correlational cross-sectional survey design (Lindakumbura, n.d.). The design was suitable because the purpose was to examine the relationship between AI tool use and postgraduate students' learning practices at one point in time. The study did not manipulate student behavior; instead, it analyzed existing survey responses from postgraduate students in Mogadishu universities.

Data were collected through an adapted questionnaire administered to postgraduate students. A total of 142 responses were received and retained after data screening. The data quality assessment confirmed 142 original records, no duplicate responses after screening, and no missing values in the main Likert-scale items, AI usage frequency, AI tools used, or AI learning activity variables. The respondent profile included postgraduate students from SIMAD University, Somali National University, Benadir University, and Hormuud University. The sample included master's and PhD students across first, second, and third years of study. The questionnaire measured demographic characteristics, frequency of AI tool use, AI tools used, learning activities supported by AI, challenges faced when using AI, and Likert-scale items related to learning practice, dependency risk, and AI integration. The main AI tools reported in the dataset were ChatGPT, Gemini, Copilot, Grammarly, and Claude. The main learning activities were research, assignments, reports, presentations, exams, and other uses.

For analysis, AI use intensity was created from three observed indicators: AI frequency score, AI tool count, and AI activity count. These indicators were standardized and combined into one AI Use Intensity variable. Learning practice was measured as the mean of five items: academic performance, assignment completion, critical thinking, study method change, and collaboration. Dependency risk was measured using technology dependency and overreliance items. AI acceptance and policy support were measured using items about the future role of AI and university AI integration.

The data were analyzed using Python. Descriptive statistics were used to summarize the sample, AI tool use, learning activities, challenges, and mean scores. Reliability was assessed using Cronbach's alpha. Pearson correlation was used to examine associations between AI use intensity and learning practice variables. Ordinary least squares regression was used to test whether the intensity of AI use predicted overall learning practices as well as each individual learning dimension. Structural modeling was discarded because the reliability coefficients indicated unstable latent constructs. Therefore, the final analysis relies on descriptive, correlation, and regression evidence.

## 4. Results and Discussion

### 4.1 Data Quality and Sample Overview

This section presents the findings of the study in sequence, organized so that each table or figure is presented together with its explanation and discussion before the next table or figure is introduced. The analysis covers data quality verification, respondent demographics, AI tool use patterns, learning activities, descriptive statistics of the study variables, reliability of the measurement scales, correlation analysis, and regression modelling. This sequence ensures that empirical results are presented with transparent interpretation and that each finding is contextualized within the study's theoretical framework, research objectives, and existing literature before proceeding to the next set of results.

Table 1 presents the data quality summary for the study dataset. The dataset comprised 142 original rows (respondents) and 23 original columns (variables). After duplicate screening, 142 rows were retained, confirming that no duplicate responses were identified. Following the removal of empty or redundant columns, the cleaned dataset contained 48 columns representing the full range of study variables. Critically, there were no missing values in the main Likert-scale items measuring learning practice, dependency risk, or AI acceptance and policy support, nor in the AI frequency, AI tools, or AI activities variables. This data quality profile supports the reliability of the subsequent descriptive and inferential analyses, and it confirms that the sample of 142 valid responses provides a complete dataset without the need for imputation or listwise deletion, which could have introduced bias into the regression estimates (Deng et al., 2025).

Table 1: Data Quality Summary

| Item                                 | Value |
|--------------------------------------|-------|
| Original rows                        | 142   |
| Original columns                     | 23    |
| Rows after duplicate removal         | 142   |
| Columns after removing empty columns | 48    |
| Missing values in main Likert items  | 0     |
| Missing values in AI frequency       | 0     |
| Missing values in AI tools           | 0     |
| Missing values in AI activities      | 0     |

**Note:** The values above reflect the dataset as used in the final analysis after data screening

Table 2 summarizes the demographic characteristics of the 142 postgraduate student respondents drawn from four Mogadishu universities. In terms of age, the largest group was aged 41 and above (28.17%), followed by two equal groups aged 26–30 and 31–35 (each 19.72%), then 36–40 (19.01%), and finally the youngest cohort aged 20–25 (13.38%). This age distribution indicates that the sample is skewed toward mature and mid-career postgraduate students, which is consistent with the Somali higher education context, where postgraduate

study is often pursued alongside professional employment rather than immediately after undergraduate completion (Abdi & Abdullahi, 2026).

Gender distribution was nearly balanced: males constituted 51.41% of respondents and females 48.59%. This near-parity is noteworthy in the Somali context, where female participation in postgraduate education has historically been constrained by structural, economic, and social barriers (Wehlie et al., 2026). The balanced gender distribution strengthens the generalizability of the study's findings across genders.

Regarding institutional affiliation, SIMAD University provided the largest share of respondents (33.10%), followed by Somali National University (28.87%), Benadir University (19.72%), and Hormuud University (18.31%). This multi-institutional profile ensures that the findings are not limited to a single institutional culture or academic context, which is an important consideration for Mogadishu-level generalizability. The program-level breakdown shows that PhD students constituted the slight majority (53.52%) over master's students (46.48%), while year-of-study distribution was relatively even across first (35.21%), second (28.87%), and third (35.92%) years. This distribution means that the sample captured postgraduate students at various stages of their academic programs, providing a cross-sectional representation of the postgraduate experience with AI tools at different levels of academic socialization.

Table 2: Demographic Profile of Respondents

| Variable      | Category                   | Frequency | Percentage |
|---------------|----------------------------|-----------|------------|
| Age           | 41 and above               | 40        | 28.17      |
| Age           | 26 - 30                    | 28        | 19.72      |
| Age           | 31 - 35                    | 28        | 19.72      |
| Age           | 36 - 40                    | 27        | 19.01      |
| Age           | 20 - 25                    | 19        | 13.38      |
| Gender        | Male                       | 73        | 51.41      |
| Gender        | Female                     | 69        | 48.59      |
| University    | SIMAD University           | 47        | 33.10      |
| University    | Somali National University | 41        | 28.87      |
| University    | Benadir University         | 28        | 19.72      |
| University    | Hormuud University         | 26        | 18.31      |
| Program Level | PhD                        | 76        | 53.52      |
| Program Level | Master's                   | 66        | 46.48      |
| Year of Study | 3rd                        | 51        | 35.92      |
| Year of Study | 1st                        | 50        | 35.21      |
| Year of Study | 2nd                        | 41        | 28.87      |

**Note:** Percentages are based on 142 valid responses.

## 4.2 AI Tool Use Patterns

Table 3 presents the frequency of AI tool use and the distribution of specific AI tools reported by the 142 respondents. In terms of frequency, 56 students (39.44%) reported daily academic use of AI tools, while 45 (31.69%) reported monthly use and 41 (28.87%) reported weekly use. The complete absence of "never" or "rarely" response categories in the frequency distribution is significant: it confirms that the study sample comprised active AI users, which is an inherent characteristic of the dataset rather than a limitation. This usage profile is consistent with the growing global prevalence of AI tools in higher education, particularly among postgraduate

students who engage with complex academic tasks requiring research support, writing assistance, and information retrieval (Ibrahim et al., 2026).

ChatGPT was the dominant AI tool, selected by 106 respondents (74.65%), which reflects its global pre-eminence among generative AI tools and aligns with findings from other studies reporting ChatGPT as the most widely adopted AI tool in academic contexts (Strzelecki, 2024; Kasneci et al., 2023). Gemini and Copilot were each selected by 62 respondents (43.66%), while Grammarly was used by 48 respondents (33.80%), and Claude by 25 respondents (17.61%). The multi-tool adoption pattern, made possible by the multiple-response format, suggests that postgraduate students in Mogadishu do not limit themselves to a single AI tool but draw on a portfolio of tools with different functional strengths — from generative text production (ChatGPT, Copilot, Claude) to writing enhancement (Grammarly) and multimodal assistance (Gemini). This finding is consistent with the Technology Acceptance Model's proposition that perceived usefulness drives technology adoption: students appear to have adopted multiple AI tools because each addresses a distinct functional need within their academic work (Davis, 1989).

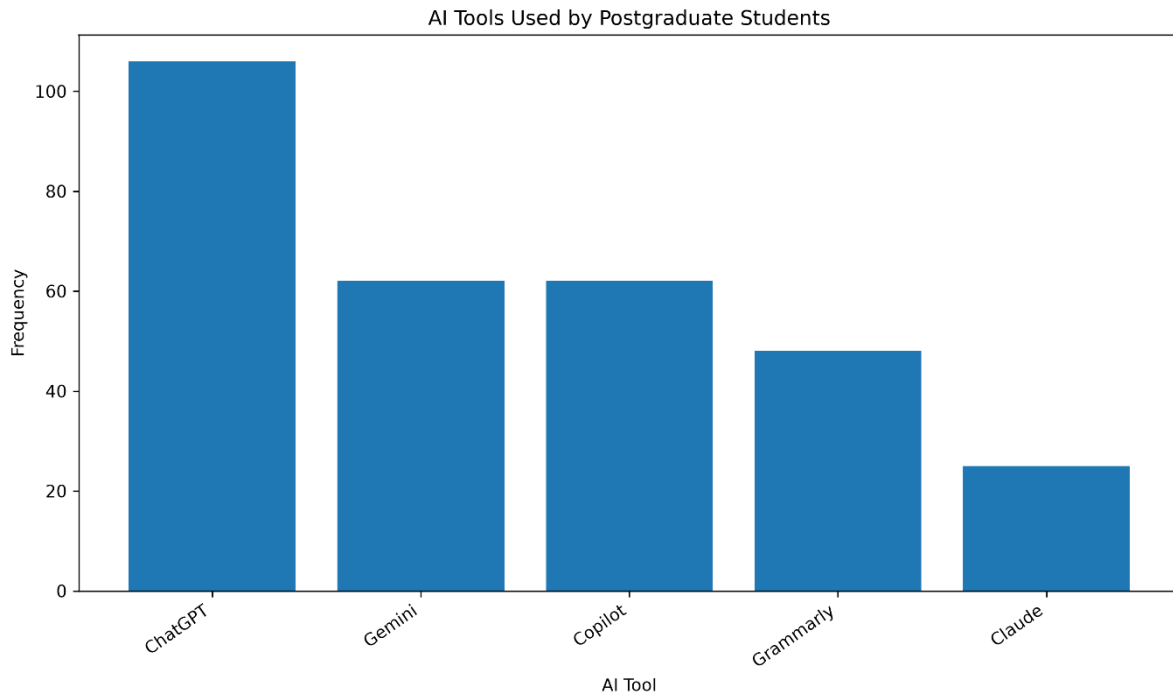
Table 3: AI Use Frequency and AI Tools Used

| Variable         | Category  | Frequency | Percentage |
|------------------|-----------|-----------|------------|
| Frequency of use | Daily     | 56        | 39.44      |
| Frequency of use | Monthly   | 45        | 31.69      |
| Frequency of use | Weekly    | 41        | 28.87      |
| AI tool used     | ChatGPT   | 106       | 74.65      |
| AI tool used     | Gemini    | 62        | 43.66      |
| AI tool used     | Copilot   | 62        | 43.66      |
| AI tool used     | Grammarly | 48        | 33.80      |
| AI tool used     | Claude    | 25        | 17.61      |

**Note:** Multiple responses were allowed for AI tools; therefore, percentages may exceed 100% across tools.

Figure 1 presents the distribution of AI tools used by postgraduate students visually, complementing the frequency data in Table 3. The bar chart clearly illustrates ChatGPT's dominance at 74.65%, well ahead of Gemini and Copilot (each 43.66%), Grammarly (33.80%), and Claude (17.61%). This visual representation reinforces the finding that while several AI tools are in active use among Mogadishu postgraduate students, the ecosystem is not evenly distributed. The adoption gap between ChatGPT and the remaining tools may reflect global brand recognition, accessibility, and the perceived competence of ChatGPT for academic text generation tasks. Future research should examine whether differential tool use is associated with different learning or productivity outcomes, given that each tool operates on different architectures and was designed with different primary use cases.

Figure 1: AI Tools Used by Postgraduate Students



***Note:** Multiple responses were allowed;  $n = 142$ . Bars represent percentage of respondents selecting each tool.*

### 4.3 Learning Activities and Challenges

Table 4 presents the learning activities for which respondents used AI tools and the challenges they encountered. Research was the most frequently reported activity, selected by 101 respondents (71.13%), followed by assignments (49.30%) and reports (43.66%). Other uses were reported by 41 respondents (28.87%), while presentations and exams were each selected by 31 respondents (21.83%). The dominance of research as the primary AI-supported activity is theoretically significant: postgraduate students are primarily engaged in research-intensive academic work, and AI tools appear to be adopted most strongly where the cognitive demands of information retrieval, synthesis, and literature engagement are highest. This pattern is consistent with Ibrahim et al. (2026), who demonstrated that generative AI supports cognitive and research-related tasks among postgraduate students, and with Mudenda (2025), who documented AI's expanding role in supporting academic production across higher education contexts.

The challenge profile reveals that postgraduate students are not uncritical users of AI tools. Ethical concerns were the most frequently reported challenge (40 respondents, 28.17%), followed closely by high cost (38 respondents, 26.76%), and both lack of training and other challenges tied at 32 respondents (22.54%) each. The prominence of ethical concerns aligns with broader international debates about academic integrity, plagiarism, and the appropriate boundaries of AI use in scholarly work, issues explicitly flagged by Kasneci et al. (2023) and Abdi and Abdullahi (2026) in the Somali context specifically. The cost barrier reflects a structural access inequality particularly salient in low-resource settings such as Mogadishu, where premium AI tool subscriptions may be financially prohibitive for students. The lack of training challenge is consistent with Self-Regulated Learning Theory (Zimmerman, 2002), which emphasizes that effective use of learning tools requires metacognitive awareness and skill development that does not emerge automatically from access alone.

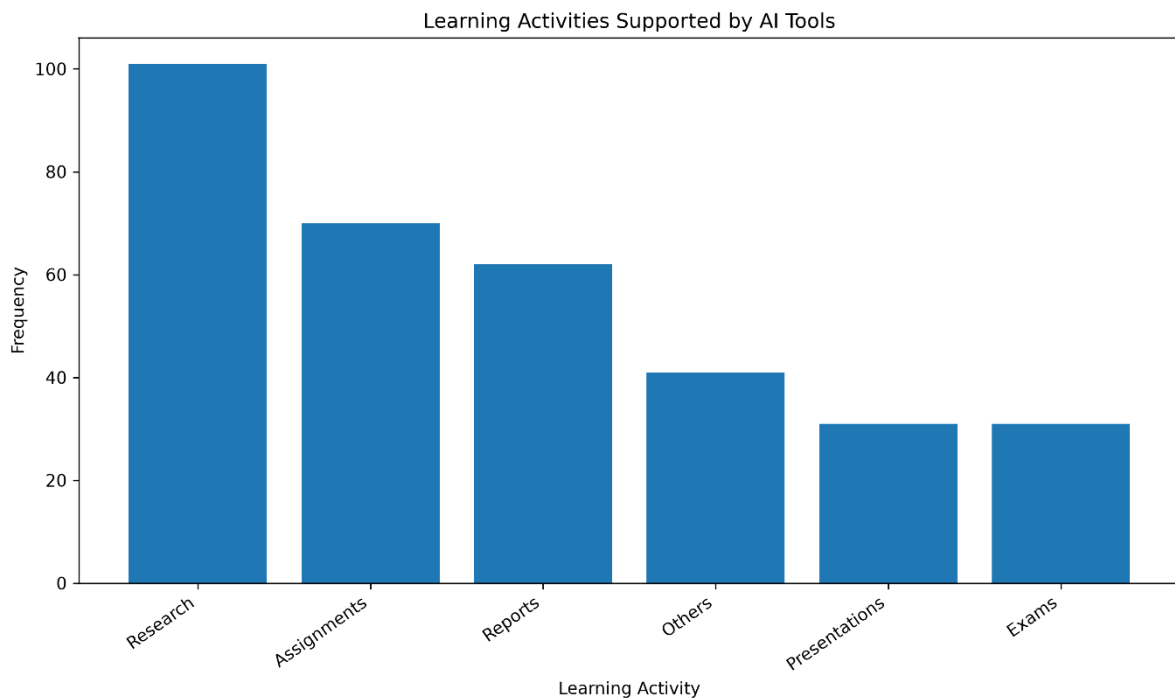
Table 4: Learning Activities Supported by AI and Challenges Faced

| Variable          | Category         | Frequency | Percentage |
|-------------------|------------------|-----------|------------|
| Learning activity | Research         | 101       | 71.13      |
| Learning activity | Assignments      | 70        | 49.30      |
| Learning activity | Reports          | 62        | 43.66      |
| Learning activity | Others           | 41        | 28.87      |
| Learning activity | Presentations    | 31        | 21.83      |
| Learning activity | Exams            | 31        | 21.83      |
| Challenge         | Ethical concerns | 40        | 28.17      |
| Challenge         | High cost        | 38        | 26.76      |
| Challenge         | Others           | 32        | 22.54      |
| Challenge         | Lack of training | 32        | 22.54      |

**Note:** Multiple responses were allowed; therefore, percentages may exceed 100% within learning activities and challenges.

Figure 2 provides a visual representation of the distribution of learning activities supported by AI tools. The figure confirms the hierarchy reported in Table 4, with research occupying a clearly dominant position relative to other activities. The visual comparison of bar heights clarifies the large gap between research (71.13%) and the next most frequent activity, assignments (49.30%), and further illustrates the relatively lower use of AI for presentations and exams (each 21.83%). This pattern supports the interpretation that postgraduate students in Mogadishu are using AI tools primarily for knowledge-production activities (research, assignments, reports) rather than for assessment performance activities (exams), which may suggest that students are more comfortable or more reliant on AI for sustained academic work than for timed evaluative tasks.

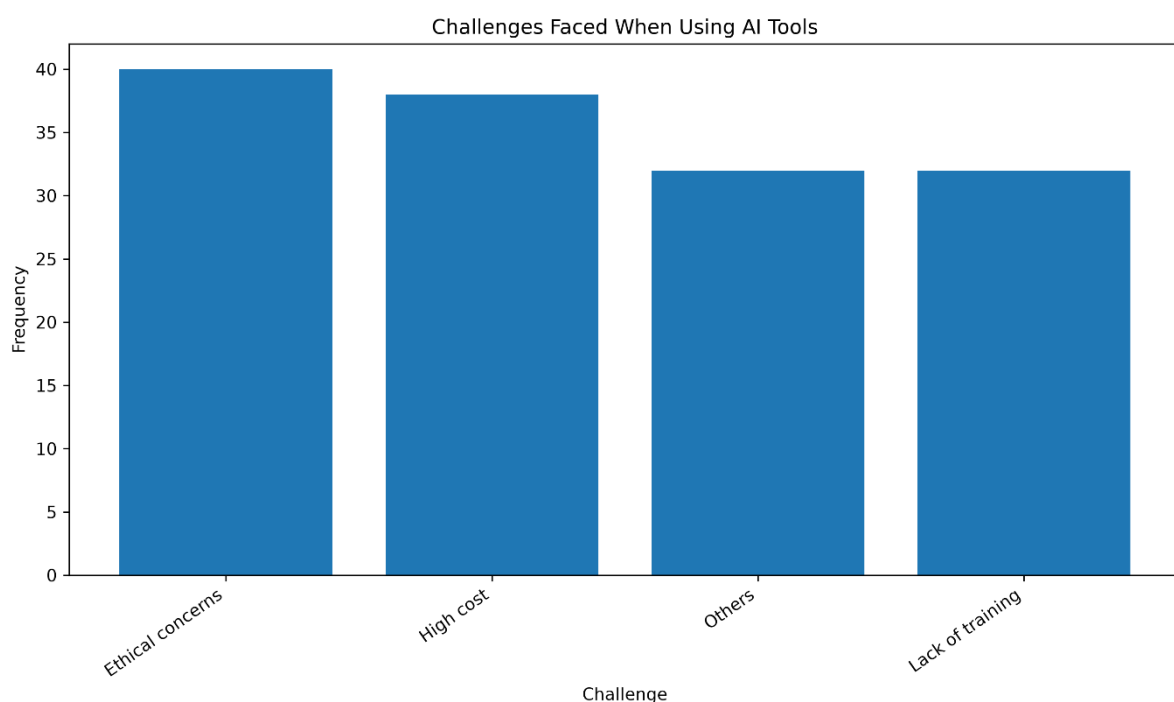
Figure 2: Learning Activities Supported by AI Tools



**Note:** Multiple responses were allowed;  $n = 142$ .

Figure 3 visualizes the distribution of challenges reported by respondents when using AI tools. The relatively even distribution of responses across the four challenge categories — ethical concerns, high cost, lack of training, and other barriers — suggests that the barriers to responsible AI use are multidimensional and cannot be addressed through a single intervention. The parity between cost and ethics as barriers underscores a dual challenge facing Mogadishu universities: addressing structural access barriers while simultaneously building the academic integrity frameworks necessary for responsible AI use. Taken together, Figures 2 and 3 indicate that while AI tools are actively used for core academic activities, the environment for their use is characterized by awareness of ethical risks, financial constraints, and gaps in formal AI literacy training — a profile that universities must address when designing AI integration policies.

Figure 3: Challenges Faced When Using AI Tools



*Note: Multiple responses were allowed;  $n = 142$ .*

#### 4.4 Descriptive Statistics of Study Variables

Table 5 reports descriptive statistics for all continuous variables used in the analysis. The AI Use Intensity variable, constructed by standardizing and averaging AI frequency score, AI tool count, and AI activity count, has a mean of 0.000 by construction (it is a standardized composite), a standard deviation of 0.592, and a range from  $-1.129$  to  $1.608$ , indicating meaningful variation in AI use intensity across respondents.

For the learning practice dimensions, all mean scores cluster in the range of 2.82 to 2.97 on a five-point scale, reflecting a neutral-to-moderate pattern. Academic performance had a mean of 2.958 (SD = 1.448), assignment completion 2.972 (SD = 1.492), critical thinking 2.824 (SD = 1.421), study method changes 2.930 (SD = 1.402), and collaboration 2.972 (SD = 1.478). The overall learning practice composite mean of 2.931 (SD = 0.637) confirms a central tendency with limited extremes, as the range of 1.400 to 4.400 shows that neither strong endorsement nor strong rejection of the learning practice items was widespread in this dataset. Dependency risk ( $M = 3.134$ , SD = 0.956) registered a notably higher mean than the learning practice dimensions. This finding is theoretically important: it suggests that respondents

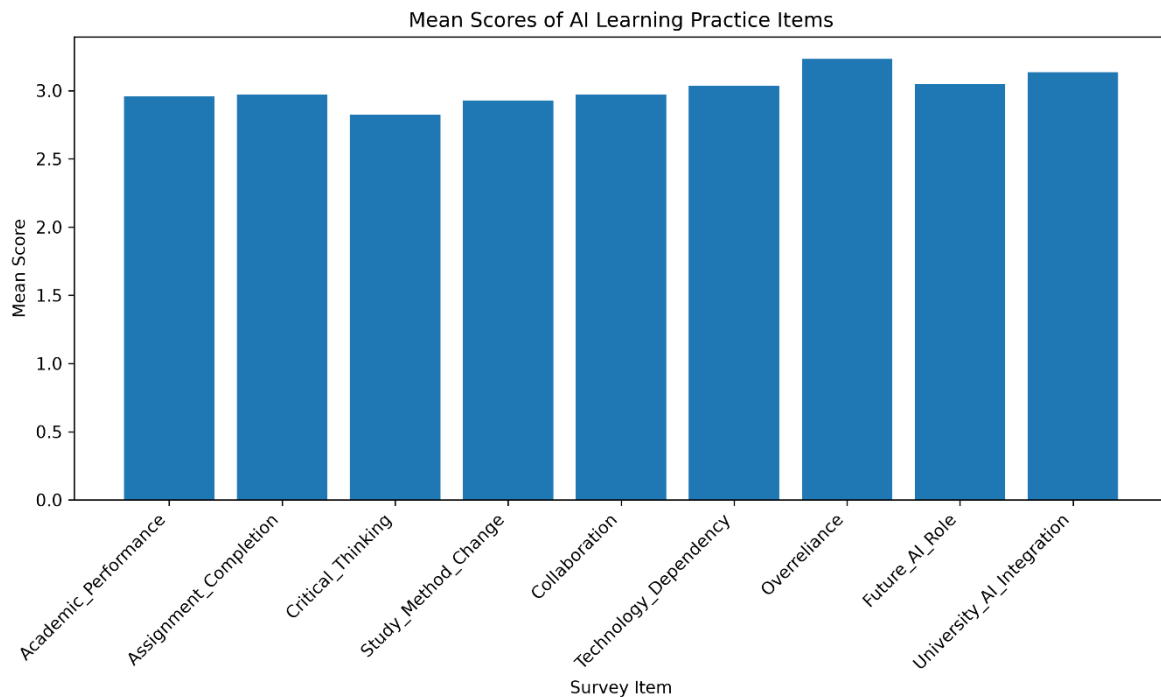
express stronger agreement with statements about technology dependency and overreliance than with statements about positive learning gains. From a Self-Regulated Learning Theory perspective (Zimmerman, 2002), this pattern is consistent with a risk profile in which AI tools are being used intensively without the metacognitive regulation that would convert AI assistance into durable learning. AI acceptance and policy support also showed a moderate mean ( $M = 3.092$ ,  $SD = 0.952$ ), indicating neither strong institutional confidence in AI integration nor strong resistance. The standard deviations across all dimensions are large relative to the five-point scale, indicating considerable individual variation in the perceived impact of AI tools — variation that the regression models would need to explain, and which the low R-squared values in subsequent tables confirm they do not substantially account for.

Table 5: Descriptive Statistics of Study Variables

| Variable              | N   | Mean  | Std. Deviation | Minimum | Maximum |
|-----------------------|-----|-------|----------------|---------|---------|
| AI_Frequency_Score    | 142 | 3.077 | 0.843          | 2.000   | 4.000   |
| AI_Tool_Count         | 142 | 2.134 | 0.977          | 1.000   | 4.000   |
| AI_Activity_Count     | 142 | 2.366 | 1.461          | 1.000   | 5.000   |
| AI_Use_Intensity      | 142 | 0.000 | 0.592          | -1.129  | 1.608   |
| Academic_Performance  | 142 | 2.958 | 1.448          | 1.000   | 5.000   |
| Assignment_Completion | 142 | 2.972 | 1.492          | 1.000   | 5.000   |
| Critical_Thinking     | 142 | 2.824 | 1.421          | 1.000   | 5.000   |
| Study_Method_Change   | 142 | 2.930 | 1.402          | 1.000   | 5.000   |
| Collaboration         | 142 | 2.972 | 1.478          | 1.000   | 5.000   |
| Learning_Practice     | 142 | 2.931 | 0.637          | 1.400   | 4.400   |
| Dependency_Risk       | 142 | 3.134 | 0.956          | 1.000   | 5.000   |
| AI_Acceptance_Policy  | 142 | 3.092 | 0.952          | 1.000   | 5.000   |

Figure 4 presents the mean scores of the key study variables visually, facilitating comparison across constructs. The chart clearly illustrates that Dependency Risk (3.134) consistently exceeds the learning practice dimensions, all of which fall below 3.000. This visual contrast between the dependency risk mean and the learning practice means is an important finding: it suggests that in this dataset, AI use is more strongly associated with perceived dependency than with perceived learning gains. The moderate position of AI Acceptance and Policy Support (3.092) between the dependency risk and learning practice means suggests that students are cautiously accepting of AI as an academic tool without yet experiencing strong positive learning effects. This pattern is consistent with the literature warning that technology adoption in education does not automatically translate into learning improvement (Kasneci et al., 2023; Ali & Saleem Mohsin, n.d.) and that institutional guidance is necessary to convert AI access into academic value (Mwakalinga & Tweve, 2026).

Figure 4: Mean Scores of AI Use, Learning Practice, Dependency, and Policy Items



**Note:** Values plotted on a five-point scale. Learning Practice, Dependency Risk, and AI Acceptance/Policy are composite means.

#### 4.5 Reliability Analysis

Table 6 reports the internal consistency reliability coefficients for the three multi-item constructs used in this study. Cronbach's alpha for learning practice ( $\alpha = -0.041$ , 5 items), dependency risk ( $\alpha = -0.125$ , 2 items), and AI acceptance and policy support ( $\alpha = -0.211$ , 2 items) were all negative. Negative Cronbach's alpha values are technically possible and indicate that the items within each construct are not positively intercorrelated as assumed by classical test theory, violating the assumption that items share a common latent factor. Conventional thresholds require alpha to exceed 0.70 for a scale to be considered sufficiently reliable for research use (Nunnally, 1978). None of the constructs in this study meets that threshold.

This finding has important methodological implications for the interpretation of all subsequent results. The composite mean scores reported in Table 5 and the correlation and regression outcomes reported in Tables 7–9 must be interpreted at the item level or as observed score aggregates rather than as indicators of stable latent constructs. The weak reliability does not invalidate the study; rather, it shifts the interpretive emphasis toward the individual item-level descriptive findings and the observed regression coefficients. Structurally, the weak reliability also explains the decision to abandon structural equation modelling in favor of OLS regression, as latent variable modelling requires reliable multi-item scales to produce stable and interpretable factor loadings. The reliability problem is acknowledged as a substantive limitation of this study that future research in the Somali higher education context should address through more careful instrument development, pilot testing, and item revision.

Table 6: Reliability Results

| Construct                        | Items                  | Number of Items | Cronbach Alpha | Interpretation |
|----------------------------------|------------------------|-----------------|----------------|----------------|
| Learning Practice                | Q9, Q10, Q11, Q12, Q13 | 5               | -0.041         | Weak           |
| Dependency Risk                  | Q14, Q16               | 2               | -0.125         | Weak           |
| AI Acceptance and Policy Support | Q17, Q18               | 2               | -0.211         | Weak           |

**Note:** Negative alpha values indicate weak internal consistency; composite-scale interpretation should be cautious.

#### 4.6 Correlation Analysis

Table 7 presents the Pearson correlation coefficients between AI Use Intensity and each of the study's outcome variables. The correlation between AI Use Intensity and overall Learning Practice was negative and non-significant ( $r = -0.092$ ,  $p = 0.2765$ ), indicating no meaningful linear relationship between the intensity of AI use and the overall learning practice composite. Individually, AI Use Intensity showed non-significant positive correlations with academic performance ( $r = 0.100$ ,  $p = 0.2355$ ) and study method change ( $r = 0.058$ ,  $p = 0.4905$ ), and non-significant negative correlations with critical thinking ( $r = -0.143$ ,  $p = 0.0905$ ) and collaboration ( $r = -0.021$ ,  $p = 0.8076$ ). AI Use Intensity was also non-significantly associated with dependency risk ( $r = 0.118$ ,  $p = 0.1619$ ) and AI acceptance and policy support ( $r = -0.014$ ,  $p = 0.8676$ ).

The single statistically significant correlation was between AI Use Intensity and assignment completion ( $r = -0.192$ ,  $p = 0.0219$ ), a weak negative relationship indicating that higher AI use intensity was associated with lower self-reported assignment completion scores. This finding does not support the view that more frequent or intensive use of AI tools enhances the quality of assignment performance; if anything, the direction of the association is contrary to that expectation. A plausible interpretation, developed more fully in the regression discussion below, is that students who experience greater difficulty with assignments may resort to more intensive AI use — a pattern consistent with dependency-driven rather than learning-enhancement-driven AI adoption. These correlation results are consistent with international evidence questioning simple positive associations between AI tool adoption and learning quality (Deng et al., 2025; Sangadji, 2025) and are particularly important to document in the Somali context, where AI tools are being rapidly adopted without established institutional frameworks for guided use.

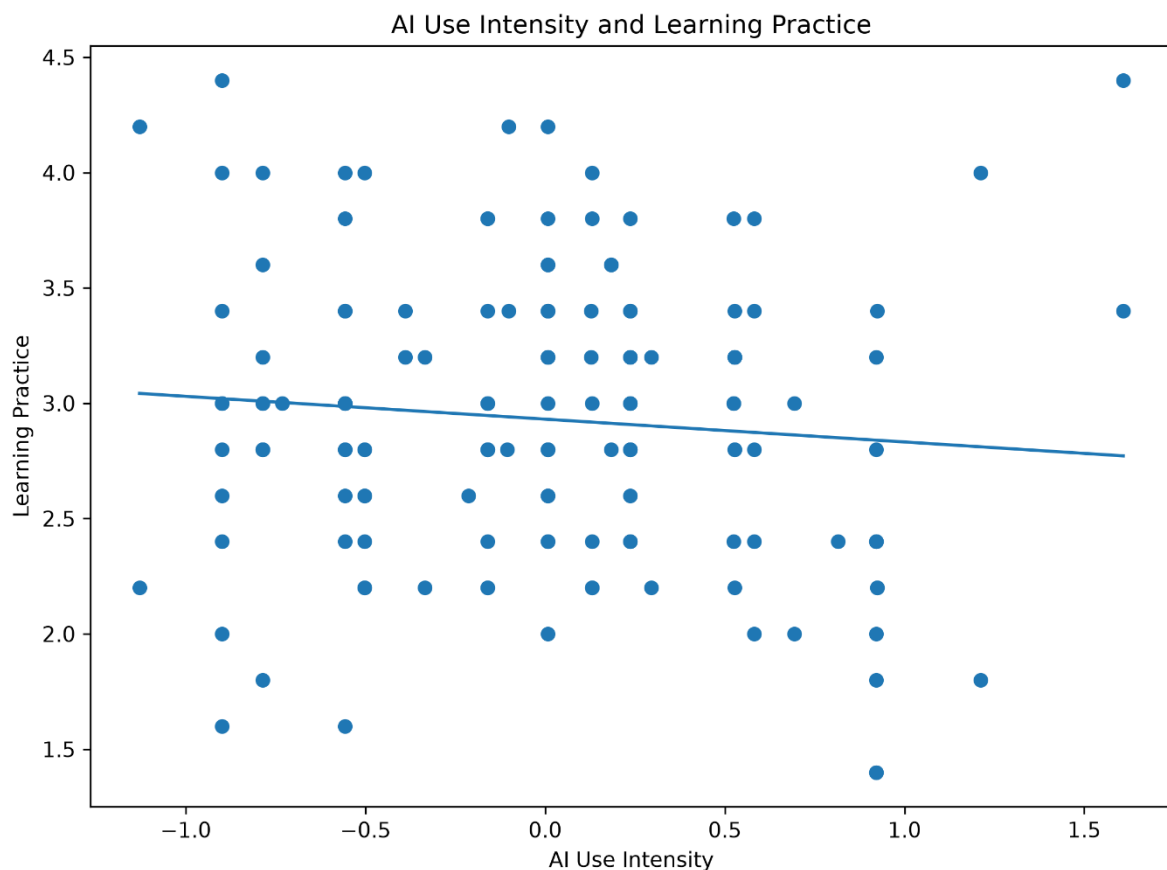
Table 7: Selected Correlations with AI Use Intensity

| Relationship          |      | Pearson r | p-value | Decision        |
|-----------------------|------|-----------|---------|-----------------|
| AI_Use_Intensity      | with | -0.092    | 0.2765  | Not significant |
| Learning Practice     |      |           |         |                 |
| AI_Use_Intensity      | with | 0.100     | 0.2355  | Not significant |
| Academic Performance  |      |           |         |                 |
| AI_Use_Intensity      | with | -0.192    | 0.0219  | Significant     |
| Assignment Completion |      |           |         |                 |
| AI_Use_Intensity      | with | -0.143    | 0.0905  | Not significant |
| Critical Thinking     |      |           |         |                 |
| AI_Use_Intensity      | with | 0.058     | 0.4905  | Not significant |
| Study Method Change   |      |           |         |                 |

|                                            |        |        |                 |
|--------------------------------------------|--------|--------|-----------------|
| AI_Use_Intensity with Collaboration        | -0.021 | 0.8076 | Not significant |
| AI_Use_Intensity with Dependency_Risk      | 0.118  | 0.1619 | Not significant |
| AI_Use_Intensity with AI_Acceptance_Policy | -0.014 | 0.8676 | Not significant |

Figure 5 presents a scatter plot illustrating the relationship between AI Use Intensity and the overall Learning Practice composite. The near-horizontal regression line visually confirms the weak and non-significant correlation reported in Table 7 ( $r = -0.092$ ,  $p = 0.2765$ ). The wide scatter of data points around the regression line reflects the high residual variance and the absence of a meaningful linear trend. This visual evidence reinforces the statistical conclusion that AI use intensity, as operationalized in this study, does not systematically explain variation in postgraduate students' learning practice. The figure is important not only for its confirmatory role but also for what it reveals about the heterogeneity of the sample: at any given level of AI use intensity, learning practice scores are widely dispersed, suggesting that factors other than AI use frequency — such as academic preparation, institutional environment, or the quality of AI integration into learning tasks — play a more important role in determining learning outcomes.

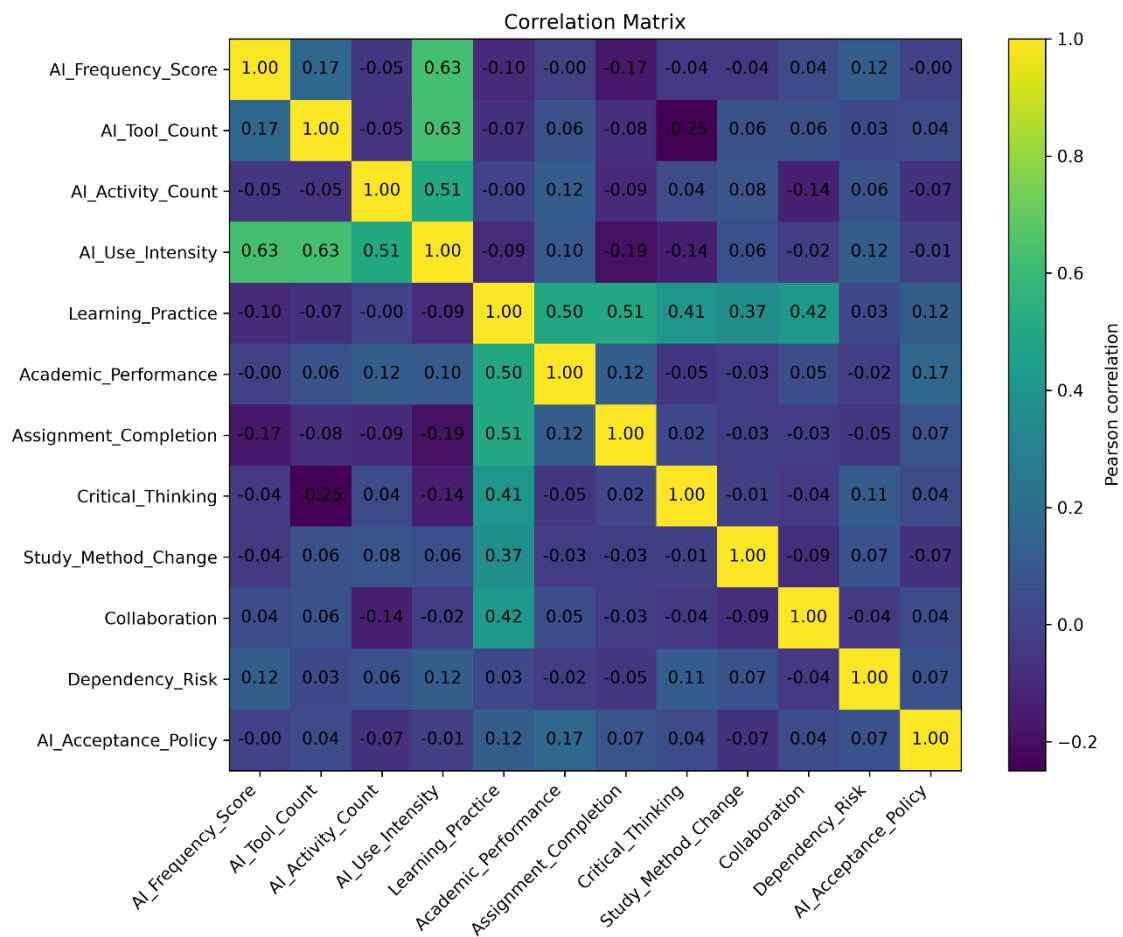
Figure 5: AI Use Intensity and Learning Practice



**Note:** Each point represents one respondent ( $n = 142$ ). The regression line shows a flat, non-significant negative trend ( $r = -0.092$ ,  $p = 0.2765$ ).

Figure 6 presents a heatmap of the full correlation matrix across all study variables. The heatmap complements Table 7 by providing a simultaneous overview of all pairwise correlations rather than focusing only on AI Use Intensity. The absence of strong color saturation across most of the matrix confirms the general pattern of weak intercorrelations among the study variables. Among the learning practice dimensions, moderate positive intercorrelations are expected within the construct (e.g., academic performance with assignment completion, or critical thinking with study method change), but any inter-correlations that are weaker than expected further explain the negative Cronbach's alpha values reported in Table 6. The heatmap also visually isolates the assignment completion and AI Use Intensity cell as the only bivariate relationship with meaningful coloring among the AI-outcome pairs, consistent with the significant negative correlation ( $r = -0.192$ ) reported in Table 7. Future research should employ a revised instrument with stronger inter-item correlations, which would produce a more coherent heatmap profile and support scale-based analysis.

Figure 6: Correlation Matrix Heatmap



**Note:** Color intensity indicates correlation strength; red = positive, blue = negative. Coefficients marked with \* are significant at  $p < 0.05$ .

#### 4.7 Main Regression Analysis

Tables 8 and 9 together present the main ordinary least squares regression model predicting overall Learning Practice from AI Use Intensity. The intercept (constant = 2.9310, SE = 0.0535,  $t = 54.834$ ,  $p < 0.001$ ) represents the predicted mean learning practice score when AI Use

Intensity is zero (i.e., at the standardized mean), confirming that the overall learning practice level in this sample is centered at a moderate score on the five-point scale. The regression coefficient for AI Use Intensity ( $\beta = -0.0989$ ,  $SE = 0.0906$ ,  $t = -1.0924$ ,  $p = 0.2765$ ) is negative and non-significant, indicating that AI use intensity does not significantly predict postgraduate students' overall learning practice in this dataset.

The model fit statistics (Table 9) further confirm this conclusion. The R-squared value of 0.0085 indicates that AI Use Intensity accounts for less than one percent of the variance in Learning Practice — an effect size that is not only statistically non-significant ( $F = 1.1934$ ,  $p = 0.2765$ ) but also trivially small in practical terms. The adjusted R-squared of 0.0014 approaches zero, indicating that the predictor provides no meaningful improvement in explaining learning practice variation beyond the intercept alone.

These results directly address the study's primary research question: the data do not support the hypothesis that more intensive use of AI tools is associated with stronger overall learning practice among postgraduate students in Mogadishu. This finding is consistent with the conclusion of Deng et al. (2025), who noted that while experimental studies show some ChatGPT-induced learning gains, observational and correlational evidence from naturalistic settings does not consistently support such effects. It also resonates with the argument advanced by Mudenda (2025) that the educational impact of AI is mediated by how students use the tools — particularly whether they engage critically with AI outputs — rather than how often they use them.

**Table 8: Main Regression Coefficients: Learning Practice Predicted by AI Use Intensity**

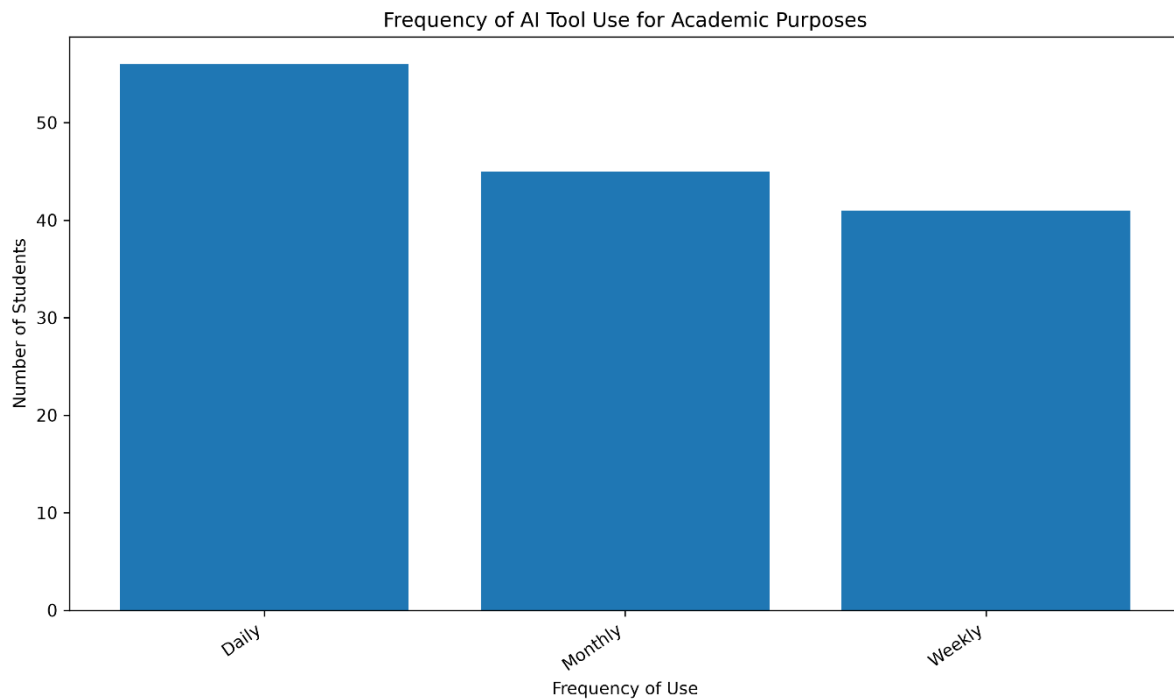
| Variable         | Coefficient | Std. Error | t-value | p-value |
|------------------|-------------|------------|---------|---------|
| const            | 2.9310      | 0.0535     | 54.8340 | <0.001  |
| AI Use Intensity | -0.0989     | 0.0906     | -1.0924 | 0.2765  |

**Table 9: Main Regression Model Fit**

| Metric             | Value  |
|--------------------|--------|
| N                  | 142    |
| R-squared          | 0.0085 |
| Adjusted R-squared | 0.0014 |
| F-statistic        | 1.1934 |
| Model p-value      | 0.2765 |

Figure 7 presents the distribution of AI tool use frequency across the sample. Daily use ( $n = 56$ , 39.44%) is the modal category, followed by monthly use ( $n = 45$ , 31.69%) and weekly use ( $n = 41$ , 28.87%). This frequency distribution is consistent with the AI Use Intensity composite and confirms that the study sample skews toward high-frequency AI use. Importantly, Figure 7 contextualizes the regression finding in Table 8: despite the high frequency of daily AI use among a significant portion of the sample, the regression model shows that this frequency does not translate into higher learning practice scores. The figure thus illustrates the empirical disconnect at the heart of the study's findings — that AI tool use is frequent and pervasive, yet its frequency is not a meaningful predictor of learning quality. This gap between access/frequency and educational benefit is a key policy implication for Mogadishu universities, highlighting the need for structured pedagogical guidance rather than reliance on frequency of use as a proxy for learning effectiveness.

Figure 7: Frequency of AI Tool Use for Academic Purposes



*Note:  $n = 142$ . Bars show number of respondents reporting each frequency level.*

#### 4.8 Overall Discussion

Taken together, the findings of this study present a nuanced and empirically grounded portrait of AI tool use among postgraduate students in Mogadishu, Somalia. AI tools — most prominently ChatGPT — are widely adopted and frequently used for research, assignment completion, and academic report writing. The demographic profile suggests that this adoption is broadly distributed across genders, age groups, institutions, program levels, and years of study. In this sense, AI tools have already become part of the normative academic infrastructure for postgraduate students in Mogadishu.

However, widespread adoption does not equate to beneficial impact on learning. The regression analyses consistently indicate that AI use intensity — as measured by frequency, number of tools, and breadth of activities — does not significantly predict stronger overall learning practice or most individual learning dimensions. The only significant regression result is a negative association with assignment completion, which is more consistent with compensatory dependency use than with learning enhancement. The mean scores reflect moderate learning practice ratings that do not rise in tandem with AI use frequency. And the dependency risk mean, which exceeds all learning practice dimension means, suggests that students are more likely to perceive themselves as dependent on AI than to perceive AI as improving their academic work.

These findings challenge a naïve techno-optimistic assumption that access to and use of AI tools will automatically improve academic outcomes in postgraduate education. This challenge is consistent with established critiques in the educational technology literature. Kasneci et al. (2023) demonstrated that large language models carry both opportunities and significant risks in educational contexts, and that the net effect depends on the quality of pedagogical integration. Zawacki-Richter et al. (2019) similarly cautioned that the educational implications of AI applications in higher education require deliberate attention to pedagogical design rather than reliance on the technology itself. Zimmerman's (2002) self-regulated

learning framework provides a theoretical explanation: students who use AI intensively without developing the metacognitive skills to evaluate, verify, and critically engage with AI outputs are likely to experience compensatory rather than transformative use patterns, which will not produce the independent academic capability that postgraduate study demands.

The reliability limitations of the measurement instrument are an important caveat that qualifies all of the above interpretations. Negative Cronbach's alpha values across all three multi-item constructs indicate that the scales as assembled in this dataset do not function as coherent psychometric instruments. Accordingly, the findings should be regarded as exploratory and descriptive rather than confirmatory, and the practical and policy implications should be treated as directions for inquiry rather than definitive conclusions. Future research in the Somali higher education context should invest in instrument development, pilot testing, and structural validation before proceeding to confirmatory analysis.

Despite these limitations, the study makes a meaningful empirical contribution by documenting, for the first time in this context, the AI use profile of postgraduate students across four Mogadishu universities and testing whether AI use intensity predicts learning practice using a full quantitative pipeline (descriptive statistics, reliability analysis, correlation, and OLS regression). The findings provide a realistic baseline against which future improvements in AI integration — driven by institutional policy, academic integrity frameworks, and AI literacy training — can be evaluated. The practical implication is unambiguous: universities in Mogadishu and similar contexts should not assume that AI tool availability or frequency of student use is sufficient for improved learning. Instead, guided, critically engaged, and ethically grounded AI use must become the institutional norm if AI tools are to fulfil their educational potential in postgraduate higher education.

## **5. Conclusion**

This study examined the influence of artificial intelligence tools on postgraduate students' learning practices in Mogadishu, Somalia. The study analyzed 142 valid survey responses, focusing on the frequency of AI use, the AI tools utilized, the learning activities involved, the challenges faced, the learning practice items, the risks of dependency, and the levels of AI acceptance and policy support. Postgraduate students widely use AI tools, as the findings indicate. ChatGPT was the most commonly used AI tool, followed by Gemini, Copilot, Grammarly, and Claude. AI tools were mainly used for research, assignments, and reports. These findings confirm that AI has become part of postgraduate academic practice in Mogadishu.

However, the regression results did not support a significant positive influence of AI use intensity on overall learning practice. AI use intensity did not significantly predict learning practice, and the model explained less than one percent of the variation in learning practice. This means that frequent or intensive AI use alone cannot be treated as evidence of improved postgraduate learning practice. The study also found that assignment completion had a significant negative association with AI use intensity. This result should be interpreted carefully because the study is cross-sectional and cannot prove causality. It may suggest that students who struggle with assignments use AI more intensively or that heavy AI use may encourage dependency rather than deeper academic work. The weak reliability results also mean that the findings should be interpreted cautiously.

The main implication is that universities should not simply encourage AI use without guidance. AI tools should be integrated through responsible AI training, academic integrity policies, verification skills, and clear rules on acceptable academic use. Postgraduate students should be trained to use AI tools as learning support, not as substitutes for reading, thinking, writing, and research judgment.

In conclusion, AI tools have become an integral part of postgraduate education and are widely used by postgraduate students in Mogadishu for various academic purposes, including conducting research, completing assignments, searching for information, and supporting learning activities. However, the evidence from this dataset indicates that higher AI use intensity does not significantly improve overall learning practice. This suggests that simply using AI tools more frequently is not enough to produce better learning outcomes. Instead, the educational value of AI depends on how effectively and critically students use these technologies, including their ability to evaluate and verify AI-generated information and apply it meaningfully in their studies. Therefore, responsible integration of AI, supported by clear institutional guidance, ethical use policies, and effective academic supervision, is necessary to ensure that AI tools enhance rather than replace independent learning, critical thinking, and academic integrity, thereby contributing more meaningfully to postgraduate learning outcomes.

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### **Ethical Approval**

This study was approved by the Institutional Review Board of Hormuud University. Written informed consent was obtained from all participants.

### **Conflict of Interest**

The author reports no conflict of interest.

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